ECG Disease Classification Using Deep Learning

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Problem Statement

- We are given annotated ECG data, i.e. ECG recordings along with the corresponding disease.
- Given a new ECG sample, we want to clasify into the different categories of disease.
- In current framework, only considered one-label classification, not multi-labeling.
- Previous work can be classified into two categories:
  - Signal Processing techniques for good feature extraction (eg. QRS peak detection) coupled with standard Machine Learning approaches.
  - Neural Networks for extraction of feature as well as for classification (eg. Convolutional Networks as there is periodicity associated)
- We want to extend the success of Neural Networks to this task as well.

Motivation

We wish to classify the disease of person based on raw ECG data.

- The main motivation comes from being able to capture real time ECG data and use that monitor the occurence of any heart related problem in the patient.
- This can also serve as a second opinion to the doctor.

Problems with Existing Methods:

- Signal Processing Techniques often may be computationally expensive and cannot work in real time.
- Need extremely high accuracy perhaps so as to not to trigger false alarms.

Heart diseases considered

The following heart diseases are considered:

- Myocardial Infarction
- Cardiomyopathy Heart failure
- Bundle branch block
- Dysrhythmia
- Myocarditis

Currently, we are bothered only with Myocardial Infarction which is major part of the PTB dataset (described next).

Methodology

The following methodology is followed:

- First we analyze using simple Convolutional Neural Networks [CNN] for our problem. CNN are a good starting point as they are well known for their spatial invariance which in 1D can be considered as the temporal invariance which is something required in a continuous ECG data.
- Next we hope to understand what things CNN is able to learn well and what it is not. In particular we want to identify some Ad-Hocs which lead to better convergence of the Neural Network.
- Then we want to know the bottleneck of the learning and what we can do to improve it, which introduces us to Graph CNN.

Dataset

The dataset used for experiments is the PTB database from Physionet repository.

- Consists of 15 channels (12 for conventional ecgs, 3 frank leads).
- Resolution is 16bit and sampling rate is 1kHz.
- Total 549 recordings from 290 subjects. 148 are diagnosed with Myocardial Infarction (MI).
- We use parts of each classification for training and rest for testing.

CNN on ECG

A simple Convolutional Network is tested on ECG.

- Architecture adopted is 1D version of the LeNet architecture. The network is :

  $$conv- > maxpool- > conv- > maxpool- > fc- > fc- > softmax$$

- Base implementation results in accuracy around 80-87%.
- Some Ad-Hocs are required to get better results.

CNN on ECG (contd.)

- Since data is not so much, each ECG data is pre-processed by taking the samples upto fixed period only (eg. 38000 points are broken into 27 partitions).
- On top of each convolution layer, we add a batch normalization. This gives accuracy boost upto 93%-94%
- State of the Art to the best of my knowledge on the PTB dataset is 96% [1]
- It is also noted that using more number of channels doesn't lead to increase in the accuracy.

We would like to do better.

Results on using CNNs on ECG

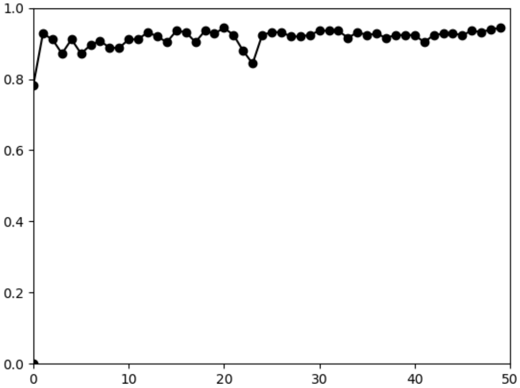

Figure: Accuracy of validation set vs Number of epochs

Exploiting Data from Different Channels

- We note that the ECG leads are put at particular locations. We would like to be able to use the underlying spatial distribution as well and incorporate data from the different leads. This is something that the standard CNN can not do.
- For this reason we go to Graph Convolutional Networks. This can be viewed as a generalization of CNN to non-euclidean spaces.
- It is not trivial to generalize CNN to non-euclidean spaces.

Graph CNN (Optional)

Two main approaches to Graph CNN

- Spectral Approach [ChebNet, NIPS2016][2]
  - Basic Idea : Use graph laplacian and do convolution operation in the spectral domain.
- Spatial Approach [MoNet, CVPR2017][3]
  - Basic Idea : Use a local manifold and learn in polar coordinates.

A limitation of Spectral Approach is that the underlying graph should be fixed, which is fortunately the case for ECG.

ChebNet (Optional)

Main Ideas in ChebNet:

- Uses graph laplacian and computes convolution in the fourier domain (using graph fourier transform).
- Restricts convolution to a local domain (k-hops) even when using the spectral approach.
- Efficient computation of the graph convoluion using the Chebyshev Polynomials.
- Efficient coarsening and pooling operation on graphs.

Main Limitation:

- The graph should be fixed. Cannot learn on multiple graphs.

ChebNet on ECG data

This is still Work In Progress. Code is ready and small bug fixes are to be made.

Main Limitations of the Approach

- Neural Networks are in general data hungry. We would need large amounts of data. Unfortunately, annotated Medical data is not very easily available.
- Data is not directly interpretable and needs the eye of a professional. Makes debugging difficult.
- In usual applications of graph convolution networks, the number of nodes can be quite high which allows for efficiently using pooling and convolutions. For a small network like ECG with only 12 nodes it remains to be seen how much improvement the Graph CNN will give over vanilla CNN.

Future Work

- Get the results on ECG data using ChebNet.
- Extend the results to larger datasets and even Holter ECG data.
- Extend the work on ECG data to EEG data as the problem space is extremely similar except for the added number of channels.

References

1. L. N. Sharma, R. K. Tripathy and S. Dandapat, "Multiscale Energy and Eigenspace Approach to Detection and Localization of Myocardial Infarction," IEEE Trans. Biomed. Eng. , vol. 62, no. 7, pp. 1827-1837, Jul. 2015
2. M. Defferrard, X. Bresson, P. Vandergheynst, Convolutional Neural Networks on Graphs with Fast Localized Spectral Filtering, NIPS 2016 (ChebNet framework)
3. F. Monti*, D. Boscaini*, J. Masci, E. Rodolà, J. Svoboda, M. M. Bronstein, Geometric deep learning on graphs and manifolds using mixture model CNNs, CVPR 2017 (MoNet framework)